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Short Communication

Improving Public Health through Good Science

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"Science can lift people out of poverty and cure disease".

- Stephen Hawking

Annually, on 7th April we celebrate World Health Day. This year's theme "Universal health coverage: everyone, everywhere" encourages all of us to participate. According to World Health Organisation (WHO), at least half of the world's population still do not have full coverage of essential health services and about 100 million people are still being pushed into "extreme poverty" (living on $1.90 or less a day) in order to pay for health care [1]. Thus, WHO has proposed tools and messages to guide and inspire everyone around the globe. Individuals, civil society and health workers should actively contribute, for instance, through clear and instant communication of needs and expectations to local policy-makers and/or through organisation of activities like discussions, concerts and interviews to provide people with an opportunity to interact and share their views related to health and health care [2]. Scientists, in my opinion, should continuously contribute through scientific excellence. Unfortunately, over the past few years, numerous concerns have been raised in regard with scientific data reproductivity, data manipulation and research bias.

In medical science data fabrication poses a direct and serious threat to human health. Data audits conducted by the US Food and Drug Administration between 1977 and 1990 found flaws in up to 20% of studies and led to 2% of clinical investigators being judged guilty of serious scientific misconduct [3]. In 2009, Fanelli reported that 2% of scientists had admitted data fabrication, falsification or modification of results at least once and around one-third of surveyed scientists had admitted other questionable research practices including "dropping data points based on a gut feeling" or "changing the design, methodology or results of a study in response to pressures from a funding source", based on the first meta-analysis of surveys (including surveys published between 1987 - 2008 and respondents form the United States in 15 studies, the United Kingdom in 3 studies, two studies of a multi-national sample and one study based in Australia) asking scientists about their experiences of misconduct [4]. The number of retracted articles from MEDLINE raised from 500 in 2014 to 684 in 2015, which is an increase of 37%, while the number of citations indexed for MEDLINE (about 806 000) has only increased by 5% (estimations based on a fiscal year not a calendar one - a fiscal year 2015 extends from October 1, 2014 through September 30, 2015) [5]. In 2016, Baker reported that 70% of researchers had failed to duplicate at least one other scientist's experiment and 50% had failed to reproduce their own experiments (based on an online *Nature's* survey of 1576 researchers). More than 60% of respondents claimed "pressure to publish" and "selective reporting" should be blamed for [6].

Are all these numbers trustworthy? Human beings are erroneous by nature; yet clinical investigators need solid preclinical studies to build upon. The analysis of survey-based data is always open to alternative interpretations, however medical respondents might be more aware of the problem. The social and legal consequences of misconduct in medical research might also highly motivate scientists to declare it [4]. On the other hand, positive replications are rarely published and journals are especially unwilling to publish negative findings. Researchers who had managed to publish a failed replication explained that both reviewers and editors required that the comparisons with the original study should be played down [7]. Thus, the false pursuit of novelty is often pinpointed as one of the key reasons of drawing false-positive conclusions. Should we also blame research founders aiming to secure their investments, highly indexed journals aiming to publish the most exciting breakthroughs and universities measuring fruition in grants obtained and papers published [8]?

Sole criticism is undoubtedly counterproductive. Sufficient and long-lasting solutions should be globally introduced instead of discouraging younger generations from research in general. "More robust experimental design", "better statistics" and "better mentorship" were recently suggested as key approaches for amendment by the majority of *Nature's* respondents [6]. In fact, statistics matters a lot, especially in the era of big data. Insufficient training in statistics and data analysis have been responsible for the retraction of high-profile papers as well as the cancellation of clinical trials. Our ability to generate data has grown dramatically but our ability to understand them has not developed at the same rate. According to Peng, an improved data science education together with improved evidence-based data analysis practices, have the potential to prevent problems with reproducibility before permanent damage to the credibility of science is caused [9]. Fisher., *et al.* reported that evidence-based data analysis can be used to identify weaknesses in theoretical procedures in the hands of average users and data analysts can be trained to improve detection of statistically significant results with practice [10].

Modern technology can lend us a hand as well. Recently, researchers from the University of Washington have developed an open-access browser to display, analyse and share neurological data collected through magnetic resonance imaging known as diffusion-weighted MRI. AFQ-Browser tool is a freely available online platform for uploading, visualising, analysing and sharing diffusion MRI data in a publicly accessible format, improving transparency and data-sharing methods for neurological studies [11]. Another convenient example, an algorithm to crunch through hundreds of thousands of biomedical papers in search for duplicate images was presented by a researcher from Syracuse University in New York. The algorithm is not publicly available due to the risk of triggering false allegations but instead researchers plan to license it to publishing houses [12]. Such examples are robustly growing these days and suggest an immense improvement in scientific data management. And indeed, in one of the recent surveys of researchers about research data (with over 7,700 respondents), Springer Nature found widespread eagerness to data sharing and a desire from researchers that their data are discoverable [13].

All in all, we should always bear in mind that good science is laborious, time- and money-consuming and above all, needs honesty and patience. „No amount of experimentation can ever prove me right, a single experiment can prove me wrong" is a paraphrase of Albert Einstein's words. The majority of research questions have been addressed by different teams and it is misleading to give priority to statistically significant findings of any single team. What matters most is the largeness of the high quality scientific evidence [14].

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Volume 2 Issue 2 May 2018